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Humanoid Kinematics and Dynamics: Open Questions and Future Directions

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Abstract This chapter raises open questions about kinematics and dynamics for humanoid robots, and sketches some possible future trends and directions. This requires to think about possible use cases in order to make good predictions about the future of kinematic and dynamic models. While initially bipedal walking with its conceptual challenges was of large concern, more recently applications such as service robotics, disaster mitigation, elderly care and medical robotics become more important. The chapter focuses on three respective future directions and argues that, first, novel concepts in mechatronics have to embrace modularity, failure tolerance and to focus on durability and endurance, concepts that may lead to a larger parameter variance in the mechanisms. Second, it is expected that real-time simulation will play a larger role and may even be included in the control loops, while coupling elastic, hydraulic or pneumatic elements with the multibody dynamics. Third, the chapter makes the prediction that the hybrid combination of data-driven and classical modeling will be key towards becoming more flexible and possibly including more soft elements also in humanoid robots. The chapter concludes with the prediction that the future of kinematic and dynamic modeling is to combine advances in classical rigid-body computations with soft mechatronics, real-time simulation, and a mix of fast computing of classical algorithms and learning methods.

1 Introduction

Kinematic and dynamic models for humanoid robots are the computational basis for simulation and control. The previous chapters discuss kinematic and dynamic modeling of humanoids from a view point of the formal multibody theory, and also from the perspective of computational efficiency. They cover important aspects of parameter estimation and calibration to make models match the effects

observed in reality. Modeling humanoid robots asks for the relation to the biomechanical models of humans. Answers are also given in these contributions.

Controlling and simulating humanoid robots is not a matter of distinct domains but an interdisciplinary endeavor. There is a substantial interplay of mechatronic design, modeling and control of such machines. To realize complex behavior such as fast bipedal walking, these disciplines need to be considered simultaneously. This concerns among others realistic sensor models, actuator models and structural properties of the robot. The rapid development of new hardware solutions might affect modeling in the future. Novel compliant actuation concepts require more advanced models, e.g., in order to simulate multibody and actuator dynamics in a comprehensive way. Novel materials as often proposed in the **soft robotics** domain [20] and recently very prominently in for robot hands [11] might lead to additional challenges, such as dealing with structural compliance. The problem of material deterioration calls for new concepts to deal with time-dependent parameter changes. Section 2 will discuss these issues.

In order to leave the laboratory environment, humanoid robots need additional capabilities besides locomotion. They need to deal with challenging environments that are partially unknown and can be sensed with only limited precision. They will have to be capable of physical interaction with humans, which imposes strong requirements on the safety of such machines. And they have to become much more endurable and operate over longer time-scales. Modeling will therefore be influenced by devising richer models of the environment and of the interacting humans. Technologically, model building is influenced and supported by several aspects. Novel kinds of computing resources such as graphics cards allow to massively parallelize algorithms. Being able to rapidly simulate complex humanoid systems has not only advantages in the control domain, but also opens a door towards applying learning approaches. A discussion on simulation enhanced modeling will be given in Section 3.

Current state-of-the art in robotics shows a clear trend to incorporate data driven learning into the modeling. Traditional model-driven approaches might reach their limits when thinking about new actuators, novel materials, parameter deterioration over time, and parameter variances in large quantities of commercial robots. Machine learning that utilizes internally more flexible and universal models is promising to alleviate these problems. Section 4 will discuss current trends in machine learning with respect to kinematic and dynamic models, and raise the question of what should be modeled in classical analytic terms and what should be learned from data. The concluding section summarizes the predictions made in this chapter.

2 Model Building and Robot Mechatronics

Most nowadays humanoid robots follow traditional mechanical design principles and well-established modeling and control concepts. In particular, humanoid robots with bipedal walking abilities are often designed with a mechanically rigid structure, connecting segments with hinge joints and bearings. A number

of robots employs parallel mechanisms, e.g., for the ankle joint [24] and hip joint actuation [41], and in some designs also in combination with elastic elements, see [14] for a representative example. However, the mechanical design of most systems is realized to match the properties of a rigid body model. This is convenient, since the mathematical formalisms of multibody kinematics and dynamics can be employed. Examples for humanoids with more creative designs can be found in the bio-mimetic robotics domain [45], such robots are usually not designed to achieving bipedal walking. In the future, mechanical designs might be influenced by novel production techniques (Rapid Prototyping), materials (Composites, smart materials) and actuation principles.

As for the structural design, future humanoid robots could be partially equipped with joints made of deformable material that seamlessly connect to the structure. Such concepts can nowadays be observed in the rapid prototyping domain, where solid structures are designed in a way to allow elastic deformations by the material itself, rather than by distinct joints. Such designs are cost-efficient, but pose challenges in modeling the joint movement: there is not a fixed rotation axis, but a load- and posture-dependent moving rotation center. This is similar to human joints, whose motion is characterized by a combination of rolling and sliding.

Incorporating structural compliance into the mechanical design offers additional advantages and therefore might be realized in humanoid robotics in the future. Current humanoids often incorporate compliant elements in the feet. In future, similar effects may be realized by a structural material compliance, which already exists in other domains such as in construction. Further, an important design objective for humanoids is to minimize structural oscillations. This is commonly realized by designing a robot structure with a high stiffness, and a low weight and inertia distribution in the distal limbs. This leads to costly hardware, e.g., based on carbon-fiber or high-strength alloys. Future trends might go to a combination of less dedicated and less expensive structural designs with novel material combinations, along with more sophisticated controls. This poses challenges on kinematic and dynamic models of such humanoids. While the theory of modeling elastic robots has been already well developed [4], it has not significantly entered the humanoid robotics research.

Since the early 2000's, Series Elastic Actuators [31], and more recently, variable impedance and damping actuators [43] have become more popular. Looking into the future, redundant actuators with antagonistic design require good models for treating variable impedance properties. Most likely, there will be more highly integrated mechatronic components, as already employed in a few recent systems, e.g., with hydraulic pipes being embedded into the robot structure. With the advent of **Soft Robotics**, novel technologies for sensing and actuation might also enter these designs.

Thinking of humanoid robots as a possible broadly sold future product, another trend could address adaptation techniques that account for aging and parameter variations of the robot hardware. Still humanoid robots are prototypical systems, produced either as unique prototypes or in small quantities.

Once produced in larger units and with cost constraints, one needs to deal with various types of deterioration. Firstly, components age, and model properties such as friction etc. will change. Secondly, there may be parameter variations in the different robot instances once they get produced in larger amounts. Online adaptation is a key to tackle this problem. Basic methodologies to this aim have been presented in previous chapters. In future, this might be complemented by machine learning approaches.

With the expectation of humanoids being applied in applications such as disaster mitigation, the aspects of maintenance and modularity becomes more important. This relates in the most simple form to being able to quickly exchange a broken module, such as an arm or leg. Kinematic and dynamic models must be able to cope with such changes, in particular if it affects properties on a larger scale. To create models for failure tolerant robots has been subject to research for industrial robots [3] and might also enter the domain of humanoids. Interesting examples for modular humanoid robots can be found in [23,15].

Applications in complex domains also ask for advanced models in terms of contact and stability. Robots need to be able to fall down and to get back up autonomously, also in narrow environments. Multi-contact models in combination with whole-body sensing are a future trend in order to realize such robustness. Current work is starting to focus on such issues [18,8]. In the humanoid robotics domain, such approaches need to deal with 3D locomotion, gait planning, multi-limb contact stability, and gait transitions. Whole body contact models might also need to be extended to cover carrying heavy loads that are in contact with many body parts (e.g. carrying a patient). Some first steps in this direction can be found in [12].

3 Internal Simulation and Predictive Models

Kinematic and dynamic models form the algorithmic basis for model-based control approaches. Due to the complexity of humanoids, realizing fast real-time control is a challenging topic. As discussed in [5], an open question is how to combine off-line computation for reducing run-time costs without excessive memory requirements or reducing the space of potential movements. Additionally, current algorithms are inherently serial, which needs to be changed when targeting to employ parallel computing hardware such as graphics cards. Progress therefore may explore the potential of parallel algorithms for humanoid kinematics and dynamics.

Besides real-time control, kinematic and dynamic models of humanoid robots are commonly used in **motion planning** algorithms. While most of these planning techniques consider kinematics only, kinodynamic **motion planning** approaches make use of dynamic models. For complex problems, such planning techniques are often based on randomized exploration, which breaks determinism and prohibits their use in strict real-time implementations. A common strategy to circumvent these issues is to solve the planning problem for short periods offline, and incorporate it into the real-time control in a receding horizon style.

The rapid progress in the parallel computation hardware will allow for a massive parallelization of randomized exploration, which paves the way to integrate complex **motion planning** problems more tightly with the control systems of humanoid robots.

Due to the algorithmic complexity, modeling for control is largely based on reduced models that cover only the major properties of the robot itself. Models of the environment, in particular of the force interaction between robot and its surrounding are often limited to the foot ground contact, and to distinct end-effectors. Progress in multibody dynamics simulation algorithms (See e.g. Chapter *Dynamics Formulation and Computation*) in combination with parallel computing hardware will allow for efficient and holistic simulations of humanoid robots. This can be an enabling factor for control concepts that comprise interactions with complex physical environments, such as whole-body grasping or heavy object transportation [12,47]. Such advances additionally allow to simulate system properties with higher accuracy, e.g., by coupling elastic, hydraulic or pneumatic elements with the multibody dynamics in a holistic way. This kind of virtual prototyping can be a promising way to support the design of humanoid robots in early stages. More realistic simulation algorithms additionally reduce the need for real robot experiments by providing a virtual test environment. This may lead to researching humanoid robot control strategies without physical hardware, which extends the humanoids communities. The Darpa Robotics Challenge (DRC) [30] is a recent example to illustrate this trend. The employed simulation environment is released under an open source license [22] and has been made available within the competition as a Cloud Computing Service. Other simulation tools suited for humanoid robots have been quickly emerging, see [17] for an overview.

Finally, and as a transition to the next section, learning algorithms for robot control will benefit from the progress in physical simulations. Once being sufficiently close to reality, data collection for the reinforcement learning methods can be realized in simulations, which eases the so-called *curse of dimensionality* and shapes the path towards learning of problems with higher complexity. First examples of this trend are focusing on learning physical navigation [38] and manipulation tasks [2].

4 Learning approaches to robot modeling

Machine learning methods have matured in recent years to a degree that they are widely available and offer a large variety of methods. These include classical regression for estimation, neural networks for model-free learning, probabilistic methods up to Gaussian processes. They embrace various learning formalisms and algorithms from error minimization to probabilistic inference. Traditionally, machine learning researchers have considered robotics a challenging domain for the application of learning algorithms and have tackled virtually all aspects of kinematics and dynamics with data-driven learning schemes.

Early works include learning of forward and inverse models often based on exhaustive exploration of the workspace through random movement under the notion of motor babbling [10,37] or online learning of a body schema, a type of forward model [16]. Also the learning of inverse kinematics by means of feedback-based learning schemes [40], through schemes resembling Jacobian-based controllers [13], under the notion of distal teachers and a feed-forward-based scheme [19], or as direct learning of inverse kinematics [35] has been considered. Finally, forward and inverse kinematics have been considered together through associative procedures [9,32,25].

Such schemes can be far from trivial. Redundancy, non-convexity of inverse kinematics, and a high number of dimensions make the problem difficult, which holds in particular for humanoid robots. An efficient and developmentally motivated online scheme for exploratory learning of direct inverse kinematics from scratch has been introduced under the notion of Goal babbling [33]. It has shown to be able to cope with significant changes in the morphology of a simulated robot [36], which is much in the spirit of more flexibility and adaptability that was discussed in the previous sections.

Forward and inverse dynamics have also been learned based on pre-recorded data [28,7] including different context (load conditions) in a single Gaussian process model. The problem of redundancy and non-convexity can be mediated by considering **model learning** only along particular trajectories that need to be tracked, along which a composition of local models can be learned very efficiently [40]. It has been shown that in a trajectory-based approach Locally Weighted Projection Regression (LWPR) [44] is currently the method of choice. See also an excellent review on **model learning** in the robotics domain [29].

All the above schemes aim at fully replacing the classical kinematic or dynamic model with a data driven approximation. In this context, humanoid robots often serve as benchmarks or to test hypotheses on human motor learning. The latter studies have a value of its own. However, given the high efficiency of a model-based approach, these learning methods are often more proof-of-concept work than being practically superior in a technical application. Clearly these approaches can not reach the accuracy of a classical modeling approach, where the mechanism is fully known and the analytical equations can be derived, while uncertainties can be tackled by parameter estimation for calibration (See Chapter *Calibration and Parameter Estimation*).

On the other hand, as discussed in the previous sections, increasingly complex and flexible mechanisms and future humanoid robots that are more soft call for data driven approaches. Either because they can hardly be modeled at all by classical means or it is just simpler and faster to track changes in the morphology, the material properties, or parameter variations through a learning approach. We expect that the rise of such **Soft Robotics** may constitute a strong future direction in humanoid robotics, whereas efficient kinematics learning has already been demonstrated [34] for a bionic arm design. The availability of such learning schemes to replace – or to complement, as discussed below – the classical analytical kinematics and dynamics will be crucial to control such

robots to a reasonable degree of accuracy. It will likely also be key to provide more freedom to the robot designers to explore novel actuation, mechanisms, or material, as discussed above.

One of the most interesting rising fields, however, is **hybrid modeling** and control. This notion refers to various intermediate schemes that try to combine the best of the classical model-based kinematics and dynamics with learning and adaptivity. There are at least three approaches, where there is active and ongoing research. Firstly, there is a number of examples that try to learn from human demonstration or kinesthetic teaching of the constraints for redundancy resolution in kinematics, e.g., the elbow position of a compliant industrial robot to improve catching objects in flight [21], or an incremental and interactive scheme to learn the free space and preferences for redundancy resolution for constraint environments [46]. Secondly, inverse optimal control and reinforcement learning try to find objective functions for movement generation from demonstrations, which in turn are used in classical optimal control schemes based on standard modeling methods for kinematics and dynamics [1,27]. These approaches provide a **hybrid modeling** in the sense that the selection mechanisms that come along with redundancy and trajectory optimization are derived from examples and then are combined with standard modeling and control.

Thirdly, there are rather novel approaches to implement a **hybrid modeling** in the sense of a combination of a coarse dynamical model together with a learned residual model. The goal is to create a hybrid controller that can operate at lower gains and can account for larger modeling errors than the analytic or learned model alone. [26] use an online Gaussian Process in a trajectory-based approach to such aim. Another scheme has been proposed under the notion of independent joint learning [42], and applied to the arm of a compliant humanoid [6], and to generalize an error model for different load conditions [39] for a compliant industrial robot.

There is a large potential to apply data driven methods and online adaptation for real world tasks, e.g., for coping with different load conditions, hardware changes, or other physical constraints and unmodeled dynamics. These methods still have to be scaled towards full body humanoids and currently can be operated only in carefully chosen scenarios. But, the principal advantage of hybrid and adaptive modeling is evident. It can allow for simplifications in the analytical model, while a learner can deal with the inevitable deviations of the real robot and real world from the modeled version. In summary, there may be two major future directions in the context of learning kinematics and dynamics. First, to develop learning methods to deal with softer robots and the lack of proper kinematics and dynamics models for these. Second, it will be a persistent research question, how to strike the balance between modeling and learning in hybrid approaches to realize the full potential of the "best of both worlds".

5 Summary

Humanoid robotics is stimulated by a rapid growth of the research domain of AI and robotics, and a rapid technological progress in computing and hardware technologies. It can therefore be expected that humanoid kinematics and dynamics will make a leap from displaying mobility aspects towards daily life tasks with rich physical environment and human interaction.

Future trends in humanoid robot technology will therefore lead to designs that are softer and more complex. This imposes challenges on kinematics and dynamics. Models will become more complex in order to cope with novel hardware designs and to account for richer physical interactions. Algorithms will become more parallel in order to exploit the capabilities of parallel computing resources. Models will become more adaptive, which leads to more learning and hybrid systems, already on the modeling level.

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